This is the published version of the following conference paper:

Nguyen Thanh, Kien, Fookes, Clinton B., Sridharan, Sridha, & Denman, Simon (2010) Focus-score weighted super-resolution for uncooperative iris recognition at a distance and on the move. In *25th International Conference of Image and Vision Computing*, 8-9 November 2010, Queenstown, New Zealand.

Focus-score weighted super-resolution for uncooperative iris recognition at a distance and on the move

K. Nguyen, C. Fookes, S. Sridharan, S. Denman

Image and Video Research Laboratory, Queensland University of Technology
2 George Street, GPO Box 2434, Brisbane, Queensland 4001
Email: kien.nguyenthanh@student.qut.edu.au, {c.fookes,s.sridharan,s.denman}@qut.edu.au

Abstract

Uncooperative iris identification systems at a distance and on the move often suffer from poor resolution and poor focus of the captured iris images. The lack of pixel resolution and well-focused images significantly degrades the iris recognition performance. This paper proposes a new approach to incorporate the focus score into a reconstruction-based super-resolution process to generate a high resolution iris image from a low resolution and focus inconsistent video sequence of an eye. A reconstruction-based technique, which can incorporate middle and high frequency components from multiple low resolution frames into one desired super-resolved frame without introducing false high frequency components, is used. A new focus assessment approach is proposed for uncooperative iris at a distance and on the move to improve performance for variations in lighting, size and occlusion. A novel fusion scheme is then proposed to incorporate the proposed focus score into the super-resolution process. The experiments conducted on the The Multiple Biometric Grand Challenge portal database shows that our proposed approach achieves an EER of 2.1%, outperforming the existing state-of-the-art averaging signal-level fusion approach by 19.2% and the robust mean super-resolution approach by 8.7%.

Keywords: iris recognition, super-resolution, signal-level fusion, MBGC

1 Introduction

Biometrics are reliable methods for the automatic identification of individuals based on their physiological and behavioural characteristics such as face, fingerprint, palmprint, gait, iris, retina, and voice. Among all the biometrics, iris has shown to be one of the most accurate traits for human identification due to its richness and stability in texture [10]. Many researchers are interested in enabling iris recognition to be conducted in a less constrained environment, such as on the move and at a distance. The most challenging problems with uncooperative iris identification at a distance and on the move are the lack of pixel resolution and noise interference such as out of focus, motion blur and frame interlacing. Super-resolution techniques have previously been employed to address the low resolution problems [15].

Super-resolution is an image processing technique that reconstructs or learns lost high-frequency information to enhance the resolution of an imaging system. Super-resolution techniques can be categorized into two classes: reconstruction-based and learning-based methods [15]. The former reconstructs lost high-frequency information by taking advantage of multiple low resolution frames of the same scene. In contrast, the latter attempts to guess the lost high-frequency information from pre-trained templates. Both methods have been utilized extensively in face image enhancement [13].

Recently, super-resolution techniques have been considered for iris resolution enhancement. Kwang et al. [18] propose a learning-based super-resolution method based on multiple MLPs (multi-layer perceptrons) for iris recognition. The proposed method restores a single low resolution image into a single high resolution image by using bilinear interpolation based on the output pixel values of the trained multiple MLPs. The middle and high frequency components of a low resolution iris image can be restored from learnt neural network architecture. Huang et al. [9] proposes another learning-based method based on CSF (Circular Symmetric Filter). Their algorithm predicts the prior relation between iris feature information of different bands and incorporates this learnt prior into the process of iris image enhancement. Both Huang et al. and Kwang et al. methods are reported to show good performance in visual and recognition enhancement. However, the robustness of iris recognition is due to the high level of distinction among different irises, the learning process can introduce fake high frequencies, which may mislead a recognition procedure. In addition, both methods are conducted in artificially-created low resolution images (low resolution iris images are produced by degrading high resolution images with Gaussian kernel and down-sampling), casting doubt as to whether it will work with real low resolution images.

From a reconstruction perspective, Falmy [5] proposes a reconstruction-based super-resolution technique to restore multiple low-resolution iris frames captured at a distance of 3 feet. The process of building a high resolution image is based on an autoregressive signature model between successive low resolution images in filling the sub pixels in the constructed high resolution image. However, Falmy's [5] approach uses the whole eye image for registration, which is potentially prone to errors due to iris dilation and contractibility properties. The situation will be worse in less constrained iris recognition applications.

The super-resolution technique has been shown to improve the performance of low resolution biometric systems [5], [9], [18]. However, uncooperative iris images at a distance and on the move also suffer from out-of-focus effect. Unfocused iris images also significantly degrade the performance of iris-based identification or verification systems. Traditionally, the focus level of an iris image will be measured to discard unfocused frames or choose the best focused frame for identification and verification [3]. A number of focus assessment methods have been proposed based on the total energy level of high frequency components in the images [3], [11], or based on a trained neural network [17]. However, instead of simply discarding low quality images, fusing quality score with the identification and verification process has been shown to improve the system performance [6].

This paper proposes a new approach to incorporate the focus score into a reconstruction-based super-resolution process to reconstruct a high resolution iris image from a low resolution and focus inconsistent video sequence of an eye. Instead of using the whole eye iris images, normalised polar-coordinate iris images are used for super-resolution to deal with iris dilation and contraction issues. The process of building a super-resolved image from the low resolution video sequence is based on reconstruction-based technique, which can incorporate middle and high frequency components from multiple low resolution frames into one desired super-resolved frame without introducing fake high frequency components. A new focus assessment approach is proposed for uncooperative iris at a distance and on the move with variation in lighting, size and occlusion. A fusion scheme to incorporate the proposed focus score into the super-resolution process is proposed. Focus scores are used to weigh the effect of each frame in the fusion stage of the super-resolution process. The in-focus frames provide a strong contribution to the final super-resolved image, while the less focused frames provide a weak contribution to the final result. This fusion approach takes advantage of all frames instead of simply discarding the unfocussed ones.

From a multibiometrics point of view, a super-resolution technique can also be considered as a multiframe signal-level fusion technique. Hollingsworth et al. proposed a signal-level fusion approach that averages multiple frames to take advantage of the temporal continuity in an iris video sequence in [8], [7]. The averaging technique has shown good performance on close-distance iris video sequences. This technique will be discussed and re-implemented here for comparison.

The Multiple Biometric Grand Challenge (MBGC) [16], which is organized by National Institute of Standards and Technology (NIST) and University of Notre Dame du Lac (UND), provides near-infrared (NIR) face portal videos recorded when participants walked through a portal located 3m from a fixed-focal-length NIR camera. This uncooperative at-a-distance and on-the-move iris database is a challenging database since the quality of video frames is variant with out-of-focus, motion blur and frame interlacing; iris region can be interfered severely by reflection, glasses, eyelids, eyelashes, shadows and participants closing or blinking their eyes in a number of frames. Examples of bad quality eye images can be found in the Figure 1.

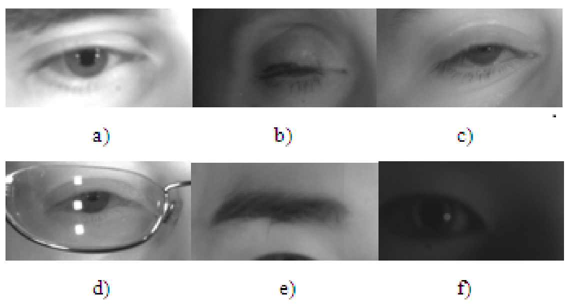


Figure 1: Bad quality eye images: a) Out of focus, b) Closed eye, c) Severely occluded by eyelids, d) Glass and reflection, e) No eye, f) Dark and low contrast.

To the best of our knowledge, this paper is the first to propose a super-resolution technique for a real low resolution, low quality iris video sequence database - the MBGC NIR iris portal database. While most other iris recognition algorithms proposed for the MBGC portal database analyse the quality and choose the best quality frame from a portal video sequence for comparison [12], our approach fuses information from all frames that are above a given focus score to take advantage of multiple frames in a video sequence. The proposed technique is also novel in the development of a focus-score driven super-resolution fusion scheme. We evaluate the proposed technique on the portal dataset within the MBGC database. The proposed technique is compared to the signal-level fusion approach proposed in [8], [7], a robust mean super-resolution approach described in [14], and a multi-gallery multi-probe baseline. It is shown that the proposed approach outperforms the other techniques, achieving an EER of 2.1%.

The remainder of this paper is organized as follows: super-resolution overview is introduced in Section 2; Section 3 describes the proposed focus-score weighted super-resolution approach for iris image enhancement; Section 4 explains our experiments on the MBGC portal database and the paper is concluded in Section 5.

2 Super-resolution overview

Super-resolution is a technique to improve the resolution of images using multiple views for recovering or learning lost high frequency components. Super-resolution techniques involve three problems: observation model design, image registration and reconstruction [15].

Observation model design

The first step in the super-resolution reconstruction problems is the formulation of an observation model, which is to develop a model that relates the high-resolution (HR) image to the observed low-resolution (LR) images. Several models have been proposed, but generally the observation model can be expressed as [15],

$$y_k = DB_kM_kx + n_k,$$

where y_k denotes LR images, D is a sub-sampling matrix, B_k is the blur matrix, M_k is the warp matrix, x is the original HR image, n_k is the additive noise that corrupts the image. Various techniques have been proposed for the reconstruction of a HR image from LR images based on above observation model. The key step in the super-resolution process is the registration between the LR source images.

Image registration

Image registration is the process of aligning two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors by geometrically aligning the images onto a common reference grid. Registering images involves defining a mapping or a transformation for pixels from the sensed to the reference image. The transformation can be modelled by the following formula,

$$I_2(x, y) = g[I_1(f(x, y))],$$

where $I_1(x, y), I_2(x, y)$ are the pixel values at coordinates (x, y) in images I_1 and I_2, f is a transformation that maps the spatial coordinates and g transforms the intensity. The registration process usually consists of the three steps: feature detection and matching, transform parameters estimation, warping. There are two classes of transformation - global and local [15]. Global methods use the same technique for the whole image while local methods treat various regions differently. Global transformations are useful when the scene is relatively static, while local transformations are suitable when objects in the scene move and change independently, such as a surveillance video.

Reconstruction-based super-resolution

Reconstruction-based methods operate directly on the pixel values of the low resolution images without prior knowledge, so these methods are generic. These algorithms can be divided into two classes: frequency domain and spatial domain [15]. Frequency domain approaches capitalize on the aliasing that exist in the LR images, an effect easily modelled in the frequency domain. The frequency domain super-resolution algorithms are superior to spatial domain methods in their theoretical simplicity. These frequency-based super-resolution methods also have low computational complexity and are suitable for parallel implementation due to the simple decoupling of the frequency domains equations. Moreover, the principal limitation of these techniques is that they limited to using global translation observation model. Numerous spatial domain reconstruction-based methods have also been proposed. Examples include non-uniform interpolation, regularized super-resolution reconstruction, projection onto convex sets, hybrid ML/MAP/POCS reconstruction, iterative back-projection and adaptive filtering [15]. These methods try to model a wide range of motions and degradations and include a prior knowledge for regularization. The flexibility however, comes at the cost of increased computational complexity.

Learning-based super-resolution

While reconstruction-based super-resolution methods try to recover lost high frequency components caused by aliasing, learning-based methods synthesize them instead [15]. A set of training images with high resolution and corresponding low resolution image patches is used to provide prior knowledge

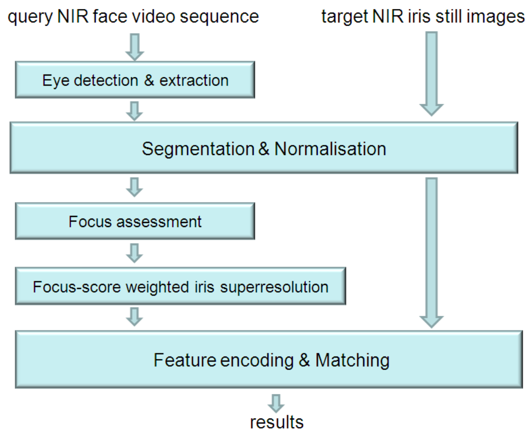


Figure 2: Flow diagram of the proposed focus-score weighted super-resolution technique for uncooperative iris recognition at a distance and on the move.

to reconstruction process. These methods almost always produce visually pleasing images due to the high frequency components created by the process. The problem is that when reconstruction error is high, the resulting super-resolution image is often still a clear image, but it may not look like the original one.

Since learning-based super-resolution techniques may introduce fake high frequencies, our proposed system will employ a reconstruction-based super-resolution technique to reconstruct a double resolution image from multiple frames of a video sequence.

3 PROPOSED FOCUS-SCORE WEIGHTED SR APPROACH

The algorithm proposed in this paper takes a NIR iris video sequence as the query input, a NIR iris still image as the target input and outputs the similarity of two. A double resolution image will be reconstructed from the NIR iris video sequence using the proposed focus-score weighted super-resolution technique. The procedure is illustrated in Figure 2. The major steps are described as follows:

1. Preprocess the video sequence: Detect and extract the eye region from each frame of the iris video sequence.

2. Segment the iris using two non-concentric circles approximation for pupillary and limbic boundaries for each frame. The segmented iris region is normalised using Daugman's doubly dimensionless projected polar coordinate [3].

3. Assess the focus level of each frame in the iris video sequence.

4. Super-resolve multiple normalised iris frames to a double resolution iris image using our proposed focus-score weighted fusion scheme.

5. Extract features using a log-Gabor filter. Match with the templates using Hamming distance as described in [3].

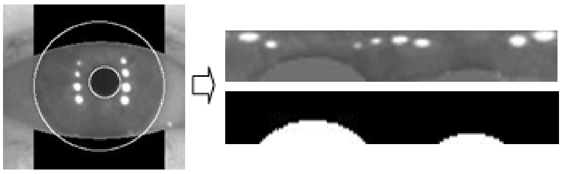
Eye regions need to be detected and extracted from the NIR face video sequence. The Viola-Jones object detector [19] is employed to identify the eye region in each face NIR frame. To detect the two-eye region in each frame in NIR face video sequence, we utilise a Haar cascade, as proposed by Castrillon-Santana et al. [1]. The eye-pair classifier has 45×11 pixels and 19 stages. To improve the searching speed, the minimum size for a two-eye region (which is 1000×300 pixels for MBGC NIR face portal database) is defined. In addition, to take advantage of a continuous video sequence, eye movement between successive frames is estimated to limit the search region. After the two-eye region is detected in each frame, the left eye and the right eye are extracted as the left and the right halves.

After the eye extraction phase, the iris region needs to be segmented and normalised. Here an iris region is considered to be the region between two non-concentric circles. Inner and outer iris circles are located using Daugman's approach [3]. Daugman's method of extracting the iris from one eye image is based on integro-differential operator acting as a circular contour detector,

$$max_{r,x_0,y_0}|G_{\sigma(r)} * \frac{\partial}{\partial r}\oint_{r,x_0,y_0}\frac{I(x,y)}{2\pi r}ds|.$$

The integro-differential operator searches over the whole image domain for the maximum in the blurred partial derivative, with respect to increasing radius, of the normalised contour integral of $I(x,y)$ along with a circular arc ds of radius r and center coordinates (x_0,y_0). The iris region can be obscured by upper and lower eyelids and eyelashes. The occlusion regions need to be excluded to retain the similarity of the probe image with the gallery image. In our approach, a parabolic curve is fitted onto edge images to find upper and lower eyelids. After the segmentation stage, the focus level of the iris region is measured by evaluating the high frequency total energy in the image (this measurement is discussed further in Section III.A). The heavily unfocused iris frames are discarded, while the others are kept for further processing. Then Daugman's doubly dimensionless projected polar coordinate [3] is exploited to normalise the iris region as shown in Figure 3. This normalisation approach is robust to variations in size and pupil dilation.

The normalised irises are used for the proposed super-resolution process (see Section III.B for details on the proposed super-resolution system). After the super-resolution stage, a super-resolved normalised iris image will be produced. The super-



a) b)

Figure 3: a) Iris segmentation using two non-concentric circles approximation, b) Iris normalisation using Daugman's doubly dimensionless projected polar coordinate. The upper is the normalised iris, the lower is the mask for occlusion.

resolved normalised iris image is encoded using a log-Gabor filter to create an IrisCode. The IrisCode is matched against IrisCode templates using Daugman's approach [3]. A Hamming distance is created to show the similarity between the query IrisCode and the template IrisCode.

In the following sections, our two contributions in focus assessment and focus-score weighted fusion for super-resolution will be outlined in detail.

3.1 Focus assessment for uncooperative iris at a distance and on the move

Due to shallow depth of field, iris frames captured from a portal typical of those used for uncooperative iris at a distance and on the move, can be out of focus, which significantly degrades the recognition performance. Severely out-of-focus iris frames need to be eliminated from the set of query images. Defocus primarily attenuates high frequency components, so the focus level of an image can be measured by high frequency energy in the image. Daugman [3] proposes a 2-D focus assessment approach which exploits a spatial 8×8 filter as depicted below to extract the middle and upper frequency band components,

-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1

Parseval's theorem shows that total power is conserved between spatial and frequency domains,

$$\int\int |I(x,y)|^2 dxdy = \int\int |F(u,v)|^2 dudv.$$

Consequently, total power of one frame in the frequency domain can be calculated by integrating the power of that frame in spatial domain after being filtered by the above high pass filter. The focus score can be normalised using the following function,

$$f(x) = x^2/(x^2+c^2),$$

where c is the energy of a "clear" image. The focus level is shown in the magnitude of the focus score with a greater magnitude indicating a greater level of focus.

Kang and Park [11] use the same approach, but they propose a 5×5 high pass filter as depicted below in lieu of Daugman's 8×8 filter. This 5×5 high pass filter is reported to reveal more high frequency components than Daugman's,

-1	-1	-1	-1	-1
-1	-1	+4	-1	-1
-1	+4	+4	+4	-1
-1	-1	+4	-1	-1
-1	-1	-1	-1	-1

The two above approaches have been shown to perform well with close-distance iris images. However, when dealing with long-distance and on-the-move iris video sequences like in the MBGC portal database, there are two factors which severely affect the accuracy of these methods: variant lighting and variant occlusion among frames. Because of the short illumination range in the recording environment of the MBGC experiments, frames are usually very bright in the middle of a video sequence, and very dark at the beginning and at the end of a video sequence. This variance in lighting alters the energy of high frequency components, which in turn alters the final focus score. In addition, the participants can blink their eyes during the capturing period. A slight movement of the eyelids can change the energy of high frequency components. Kang et al. and Daugman's methods perform poorly when dealing with these two factors.

Here, we propose a new approach for assessing the focus level of an iris image in variant lighting and variant occlusion conditions outlined by the following steps.
1. Extract the lower half of an iris region.
2. High-pass filter the lower half by Kang and Park's 5×5 filter.
3. Calculate the total energy of the filtered image in the spatial domain.
4. Calculate the normalised focus score ultilising the following novel formula,

$$FS = \frac{\sum\limits_{x=1}^{col}\sum\limits_{y=1}^{row}[I'(x,y)]^2}{\left(\frac{\sum\limits_{x=1}^{col}\sum\limits_{y=1}^{row} I(x,y)}{N}\right)^2},$$

where FS is the normalised focus score, $I(x, y)$ is the original lower half of the iris region, $I'(x, y)$ is the filtered lower half of the iris region, N is the number of pixels in the lower half of the iris region image. The denominator, which is the average of pixel intensity of the lower half of the iris region before being filtered, plays the role of a normalisation factor.

The use of only lower half of the iris region ensures the focus score is robust to eyelid movement since the lower half of iris region is less occluded by eyelid and eyelashes than the upper. The lighting variance is overcome by introducing a normalisation factor in the focus score formula. Compared with other typical illumination normalisation methods such as DCT-based [2] and wavelet-based [4] illumination normalisation, our proposed normalisation is not only less computationally expensive but also performs better, since DCT-based and wavelet-based approaches usually introduce new unexpected high frequency components after normalisation. The proposed focus score is robust to both lighting and occlusion variations.

3.2 Focus-score weighted super-resolution scheme

Fusing information details from multiple frames effectively is critical to the success of a super-resolution process. A fusion scheme is considered as 'good' when it can:
1. Incorporate various high frequency components from all frames.
2. Take advantage of different appearance of reflection and occlusion. Reflection can appear in different locations in different frames. Occlusion by eyelids and eyelashes can hide or reveal different parts of the iris in different frames.
3. Evaluate the quality of each frame and incorporate the quality into the fusion process.

The proposal by Hollingsworth et al. on averaging normalised iris images from a video sequence [7], [8], satisfies the first and second of these fusion criteria. The robust mean super-resolution approach [14] has been proposed as an improvement fusion scheme over averaging to cope with the first two criteria. In this paper, all three criteria are considered in the proposed focus-score weighted super-resolution scheme. The proposed approach is illustrated in Figure 4. The major steps are described as follows,

1. Interpolate the original normalised iris images and correspondent masks to twice the input resolution using bilinear interpolation.

2. Register the interpolated normalised iris images with the reference image by shifting the IrisCode and selecting the shift that produces the smallest Hamming distance.

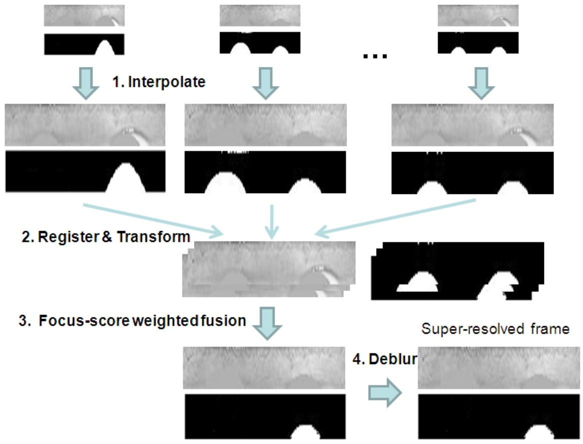


Figure 4: Proposed focus-score weighted super-resolution diagram.

3. Estimate the super-resolved image using focus-score weighted fusion scheme from the reference image and other registered images:

$$I(y, x) = \frac{\sum_{i=1}^{N} I_i(y,x) \times FS_i}{\sum_{i=1}^{N} FS_i},$$

where $I(y, x)$ is the intensity value of the pixel of the target super-resolved image at row y and column x; $I_i(y, x)$ is the intensity of the pixel at the same location of the frame number i; FS_i is the focus score of the frame number i; N is the number of frames.

4. Restore the final super-resolved image by applying a deblurring Wiener deconvolution filter. Applying a spatially invariant Wiener filter reduces the amount of noise present in an image by comparison with an estimation of the desired noiseless signal.

4 EXPERIMENTS

Iris verification experiments have been conducted on the MBGC portal database. The database consists of 628 NIR face portal video sequences recorded when participants walked through a portal located 3m from a fixed-focal-length NIR camera and 8589 NIR good-quality iris still images of 129 participants. Iris regions are extracted from each frame and fused using the proposed approach for identification against high resolution NIR iris still template images. The proposed algorithm that uses a novel focus assessment method to weigh the inputs into a reconstruction-based super-resolution algorithm is compared to the other iris recognition algorithms including Multi-Gallery Multi-Probe baseline, Averaging [8], [7] and Robust Mean super-resolution [14]. The Detection Error Trade-off (DET)

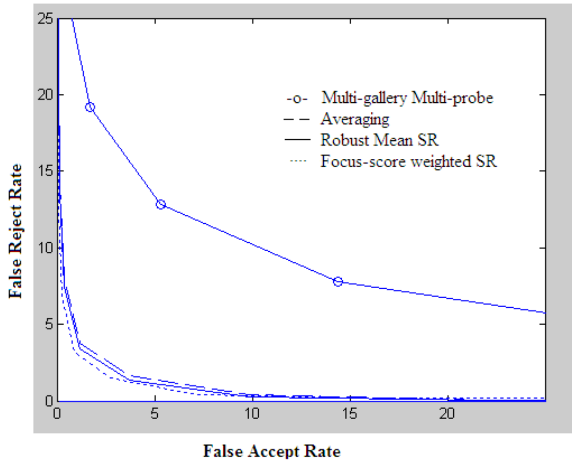


Figure 5: Performance of proposed Focus-score weighted Super-Resolution approach in comparison with Multi-Gallery Multi-Probe, Averaging and Robust Mean super-resolution.

curve plotting false rejection rate vs. false acceptance rate of these four evaluation systems is shown in Figure 5. The Equal Error Rate (EER) of all four methods is shown in Table 1.

The EER shows that the proposed method outperforms all other three methods by 79.2%, 19.2%, 8.7% respectively. The Averaging method performs better than Multi-Gallery Multi-Probe method by 74.2% since a number of outliers have been averaged. The Robust Mean super-resolution performs better than Averaging method by 11.5% since the robust mean fusion scheme is more intelligent in selecting the pixel for fusion than simply averaging. Our proposed focus-score weighted super-resolution in this paper outperforms all three methods since the focus level of each frame is incorporated into the fusion process. The proposed fusion scheme allows the sharpest frames with the most high resolution image to be given a higher weight during the fusion, whilst still allowing less focused frames that may contains regions that otherwise occluded to contribute. The methods proposed in [8], [7], [14] do not consider the quality of the frames they are using, so the information contained in sharp, well-focused images is potentially diluted by poorer quality images. The proposed focus-assessment algorithm which provides weights for the fusion enables the system to identify the high quality frames leads to the improvement in performance.

Table 1: Equal Error Rate (EER) of proposed methods in comparison with Multi-Gallery Multi-Probe, Averaging and Robust Mean Super-Resolution methods.

Methods	**EER**
Multi-Gallery Multi-Probe	10.1×10^{-2}
Averaging	2.6×10^{-2}
Robust Mean SR	2.3×10^{-2}
Proposed method	2.1×10^{-2}

5 CONCLUSIONS

This paper has shown that incorporating the focus score into the super-resolution process improves the quality of the super-resolved iris image outputs, which in turn improves recognition performance in uncooperative at-a-distance and on-the-move iris recognition applications. Our proposed focus-score weighted super-resolution approach for iris portal video sequences performs better than the existing state-of-the-art techniques, including the averaging signal-level fusion by Hollingsworth et al. as well as the robust mean super-resolution approach by Kien et al. when tested on the MBGC portal database. The proposed approach also outperforms the best-quality-frame-selection based technique proposed by Yooyoung et al..

6 ACKNOWLEDGMENTS

Our thanks to University of Notre Dame du Lac, National Institute of Standards and Technology (NIST) for allowing us to use the MBGC database in this research.

References

[1] M. Castrillón Santana, O. Déniz Suárez, D. Hernández Sosa, and J. Lorenzo Navarro. Using incremental principal component analysis to learn a gender classifier automatically. In 1st Spanish Workshop on Biometrics, Girona, Spain, June 2007.

[2] W. Chen, M. J. Er, and S. Wu. Illumination compensation and normalization for robust face recognition using discrete cosine transform in logarithm domain. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 36(2):458 –466, april 2006.

[3] J. Daugman. How iris recognition works. IEEE Transactions on Circuits and Systems for Video Technology, 14(1):21 – 30, 2004.

[4] S. Du and R. Ward. Wavelet-based illumination normalization for face recognition. In Image Processing, 2005. ICIP 2005. IEEE International Conference on, volume 2, pages II – 954–7, 11-14 2005.

[5] G. Fahmy. Super-resolution construction of iris images from a visual low resolution face video. In Signal Processing and Its Applications, 2007. ISSPA 2007. 9th International Symposium on, pages 1 –4, 12-15 2007.

[6] J. Fierrez-Aguilar, J. Ortega-Garcia, J. Gonzalez-Rodriguez, and J. Bigun. Discriminative multimodal biometric authentication based on quality measures. Pattern Recognit. (UK), 38(5):777 – 9, 2005.

[7] K. Hollingsworth, T. Peters, K. Bowyer, and P. Flynn. Iris recognition using signal-level fusion of frames from video. Information Forensics and Security, IEEE Transactions on, 4(4):837 –848, dec. 2009.

[8] K. P. Hollingsworth, K. W. Bowyer, and P. J. Flynn. Image averaging for improved iris recognition. volume 5558 LNCS, pages 1112 – 1121, Alghero, Italy, 2009.

[9] T. T. J. Huang, L. Ma and Y. Wang. Learning based resolution enhancement of iris images. British Machine Vision Conference, 1(1):1 – 10, 2003.

[10] A. Jain, A. Ross, and S. Prabhakar. An introduction to biometric recognition. Circuits and Systems for Video Technology, IEEE Transactions on, 14(1):4 – 20, jan. 2004.

[11] B. J. Kang and K. R. Park. A study on iris image restoration. pages 31 – 40, Berlin, Germany, 2005.

[12] Y. Lee, R. Micheals, and P. Phillips. Improvements in video-based automated system for iris recognition (vasir). In Motion and Video Computing, 2009. WMVC '09. Workshop on, pages 1 –8, 8-9 2009.

[13] F. Lin, C. Fookes, V. Chandran, and S. Sridharan. Super-resolved faces for improved face recognition from surveillance video. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), volume 4642 LNCS, pages 1 – 10, Seoul, Korea, Republic of, 2007.

[14] K. Nguyen, C. Fookes, and S. Sridharan. Robust mean super-resolution for less cooperative nir iris recognition at a distance and on the move. International Symposium on Information and Communication Technology, 2010.

[15] S. C. Park, M. K. Park, and M. G. Kang. Super-resolution image reconstruction: a technical overview. IEEE Signal Processing Magazine, 20(3):21 – 36, 2003.

[16] P. Phillips, P. Flynn, J. Bevcridge, W. Scruggs, A. O'Toole, D. Bolme, K. Bowyer, B. Draper, G. Givens, Y. M. Lui, H. Sahibzada, I. Scallan, J.A., and S. Weimer. Overview of the multiple biometrics grand challenge. In Advances in Biometrics. Proceedings Third International Conference, ICB 2009, pages 705 – 14, Berlin, Germany, 2009.

[17] H. Proenca and L. Alexandre. A method for the identification of noisy regions in normalized iris images. In Pattern Recognition, 2006. ICPR 2006. 18th International Conference on, volume 4, pages 405 –408, 0-0 2006.

[18] K. Y. Shin, K. R. Park, B. J. Kang, and S. J. Park. Super-resolution method based on multiple multi-layer perceptrons for iris recognition. In Ubiquitous Information Technologies Applications, 2009. ICUT '09. Proceedings of the 4th International Conference on, pages 1 –5, 20-22 2009.

[19] P. Viola and M. J. Jones. Robust real-time face detection. International Journal of Computer Vision, 57(2):137 – 154, 2004.